The Choice of Inflation Targeting*

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Abstract

This paper assesses empirically the contribution of key macroeconomic and institutional variables in shaping the likelihood of choosing the Inflation Targeting (IT) regime in a sample that comprises countries working under such a regime and covers the period 1975-2005. I find inflation rate, financial development, GDP per capita and trade openness relevant for driving the choice of IT by estimating a discrete choice panel data model. Also, my results suggest that the initial conditions at the moment of IT adoption do matter because countries have different exposure to the likelihood of choosing IT as a result of their specific macroeconomic and institutional fundamentals and unobservable idiosyncratic factors.

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1 Introduction and Motivation

Throughout history, central banks have conducted their monetary policies according to needs and conditions of their economies, sometimes by monitoring monetary aggregates, sometimes by affecting the evolution of the nominal exchange rate. Nowadays, it is well known that the main focus of monetary policy should be attaining low, stable inflation, as deviating from this objective has serious stability growth and welfare costs (Kydland and Prescott (1977)).

The IT regime is a young monetary policy scheme that emerged in the early 1990s as a monetary regime truly involved with the inflation objective in both the academic and political realms. Since its adoption by the Reserve Bank of New Zealand in 1990, an increasing number of central banks has found in IT an effective institutional arrangement for guiding private agents' expectations, improving tools for communicating policy actions, and thus, enhancing monetary policy credibility.

Central banks working under the IT regime announce inflation targets for the horizon they consider the most proper taking into account the lags with which monetary policy affects inflation and their preferences about the short-run tradeoff between output and inflation (see Gredig et al. (2007)). The role of monetary policy consists in anchoring private expectations to the target having some flexibility for doing so, and monitoring directly these expectations as the intermediate instrument in the policy framework. Indeed, the transparency on how monetary policy operates under IT makes the formation of inflation expectations easier, thereby strengthening the ability of central banks to achieve inflation targets, and therefore, prompting other central banks to mimic this practice.

Some preconditions, however, should be met in order to successfully implement such a regime. Remarkable experiences with the IT regime in place in early countries (e.g., New Zealand, Chile, Canada, United Kingdom) have served as examples for some authors (e.g., Masson et al. (1997), Mishkin and Savastano (2002); Mishkin and Schmidt-Hebbel (2002)) to propose general institutional and macroeconomic requisites central banks should observe in advance. This regime performs well if implemented by highly independent central banks, and by countries with balanced and sustainable fiscal accounts and sane and sound financial markets. These preconditions summarize the idea of a central bank that has no excuse—coming from a government with a weak capacity for self-financing or the need for bailouts in the financial system—to abandon its quality of conducting an independent monetary policy. But many of the latter preconditions are not met today even by many middle-income developing countries. Actually, Batini and Laxton (2007), contradicting the preceding literature, show that most inflation targeters (ITers for short)—including most industrial-country ITers—were far from satisfying the latter preconditions at the time they started IT. Most ITers, however, improved the underlying measures gradually after IT adoption, often taking many years before any significant improvements in economic and institutional conditions.

Yet countries differ in what they consider as the desired figures for their inflation environment, fiscal stance and financial situation prior to IT adoption. Figure 2 shows the cross-country distribution for 25 countries working under IT up to 2005[1] of measures of macroeconomic performance—depicted by inflation rate, government budget balance (surplus) and financial development—calculated over three periods: 5 years before the adoption date (pre-period), date of adoption, and 5 years after the IT adoption date (post-period).[2] Visually, for inflation rate and fiscal position there are more differences between distributions estimated for the pre-period and post-period. While in the first period (see the solid lines in blue) the inflation distribution shows a huge dispersion with the presence, apparently, of many modes, in the second period (see the solid lines in red) that distribution becomes more concentrated around one-digit inflation levels. That difference with regard to variance also applies for government budget balance, although it is more noticeable when focusing on the fifth year after the IT adoption. In this year, the distribution of government budget balance exhibits a nearly symmetric shape around zero with lower variance than other periods. In sum, this cross-country heterogeneity in macroeconomic performance leaves unclear a concrete notion for the macroeconomic preconditions listed above.

The interest for unveiling, from an empirical viewpoint, the determinants that drive the choice of IT is not new, although it is the strategy undertaken in this paper. Previous studies differ in estimation techniques, main specifications, time coverage and country samples; not surprisingly the evidence is inconclusive. But these studies are common in that they are restricted to the cross-section framework; thus, neglecting the time dimension.

Next I classify the empirical literature by the kind of variables included in the main specification. Gerlach (1991) explores the determinants behind the choice of IT by performing probit regressions but discarding the macroeconomic preconditions listed above; although the author controls for some variables deemed as structural, like trade openness and measures of credibility, and some other variables related to the volatility of real shocks. Another strand of the literature has assessed explicitly the role of the macroeconomic requirements, including Mishkin and Schmidt-Hebbel (2002), Carare and Stone (2006) and, more recently, Hu (2006). Mishkin and Schmidt-Hebbel (2002) use several measures of central bank independence and credibility as well, using a sample that comprises the last decade and a larger set of countries. Carare and Stone (2006) test the relevance of more than one dimension for both fiscal and financial preconditions in shaping the likelihood of choosing IT, using also a larger country sample. Fi-

[1]The list of these countries is shown in table 3.

[2]See table 4 for a detailed description of these variables.

nally, Hu (2006) uses a comprehensive data set for his pooled panel regressions, classifying the variables as economic structure variables—fiscal position, trade openness, external indebtedness, and financial depth—economic institutional variables—measures of central bank independence and a *de facto* classification for exchange rate regimes—and control variables like the inflation rate and the GDP growth.

Unlike the reviewed literature, in this paper I carry out a comprehensive empirical study which has the following features. First, by recognizing that the choice of IT is a process involving continuous evaluation across time, I use the panel data methodology, a useful framework to control for unobserved country heterogeneity, which is an important issue, as discussed above. Second, I discuss carefully the econometric estimation approach, presenting some simulation results that are intended to support the analysis. Third, I perform robustness checks by running regressions for different specifications. Finally, I use a set of variables covering the key dimensions of the analysis surrounding the IT adoption evaluation in practice. Note that the results described in this paper are only valid for comparing IT experiences before and after the IT adoption. They do not generalize to any country that has no such a regime in place.

This paper is organized as follows. In the next section I expose the econometric issues underpinning the empirical strategy. I propose discrete choice models in a panel data framework (estimated by the Maximun Likelihood Estimator, MLE for short) and explore issues related to the asymptotic plan, the time series properties of my right-hand-side variables and the potential endogeneity problems that could arise. In section 3 I perform data analysis in two fronts: cross and pooled correlation analysis—motivated by the potential presence of collinearity among regressors—and a variance decomposition analysis for the regressors—which tries to support the way I choose to estimate panel data discrete choice models. In section 4 I report the results coming from the main specification and the robustness checking. Section 5 concludes. Finally, the results of the Monte Carlo study that is intended to shed some light on the large sample properties of the MLE under different conditions—discussed in section 2—are displayed in the Appendix.

2 Econometric Analysis

As I am interested in explaining the likelihood of adopting IT, let y_{it} be a binary variable whose value depends on a latent variable y^*_{it} in the following manner:

$$y_{it} = \mathbf{1}(y^*_{it} \geq 0) \tag{1}$$

where $\mathbf{1}(\cdot)$ is the indicator function which is 1 if country i chooses IT in period t and 0 otherwise. Moreover,

$$y_{it}^* = \eta_i + \alpha y_{i(t-1)} + x_{it}'\beta + \varepsilon_{it} \tag{2}$$

η_i is the individual effect which is supposed to capture any source of unobserved heterogeneity, while α and β are fixed and common parameters for all individuals. The influence of the past decisions on the current choice motivates the inclusion of $y_{i(t-1)}$. In the microeconometric literature, α measures choice persistence (true dependence) while η_i represents persistence due to individual heterogeneity which remains constant through time (spurious dependence). x_{it} is a set of possible macroeconomic and structural explanatory exogenous variables. Finally, ε_{it} stands for all sources of variation—across individuals and time—I am unable to model.[3]

I restate the main equation by combining (1) and (2), obtaining:

$$y_{it} = \mathbf{1}(\eta_i + \alpha y_{i(t-1)} + x_{it}'\beta + \varepsilon_{it} \geq 0). \tag{3}$$

Equation (1), however, is useful for making clear that the choice of a regime involves a utility or welfare evaluation. Precisely, y_{it}^* is the utility indicator which drives country i in time t to choose IT as the preferred monetary policy framework—relative to the option of not adopting it—if the chosen framework reports a gain in comparison with the alternative (that is, if $y_{it}^* \geq 0$).

In principle, this dynamic specification is the most proper to deal with a choice behavior which assigns to the current evaluation a high weight to the choice made in the past. In practice, the adoption of a monetary regime entails a complicated and long process of evaluation of benefits and costs based on the regime's performance dictated by past experience.

But this continuous evaluation does not imply countries make decisions erratically about the most suitable economic policy. They exhibit, instead, a persistent behavior. A review of the IT experiences reveals that no country has abandoned it[4], a stylized fact that has non-trivial consequences in my econometric specification.

Let me explain why this happens with the aid of a simplified version of (3). For this purpose consider the following first-order Markov chain:

$$y_{it} = \mathbf{1}(\eta_i + \alpha y_{i(t-1)} + \varepsilon_{it} \geq 0). \tag{4}$$

This Markovian process has four states. A country must decide between adopting or not adopting IT after it made a similar decision in the previous period. Hence, the conditional probabilities associated to this process, generally denoted by $P_{ss'}$ representing the likelihood of transiting from state s' to state s, are the following:

[3] I could include time effects in (2), accounting for international shocks such as the oil price shock.

[4] Spain and Finland abandoned IT in 1998 but as a natural implication of the conformation of the Euro Area.

$$\mathcal{P}_{10}(y_{it} = 1|\eta_i, \alpha, y_{i(t-1)} = 0) = \mathcal{F}(\eta_i) \tag{5}$$
$$\mathcal{P}_{00}(y_{it} = 0|\eta_i, \alpha, y_{i(t-1)} = 0) = 1 - \mathcal{F}(\eta_i) \tag{6}$$
$$\mathcal{P}_{11}(y_{it} = 1|\eta_i, \alpha, y_{i(t-1)} = 1) = \mathcal{F}(\eta_i + \alpha y_{i(t-1)}) \tag{7}$$
$$\mathcal{P}_{01}(y_{it} = 0|\eta_i, \alpha, y_{i(t-1)} = 1) = 1 - \mathcal{F}(\eta_i + \alpha y_{i(t-1)}) \tag{8}$$

where $\mathcal{F}$ is the probability distribution assumed for ε_{it}. Unfortunately, I do not observe in my country sample the event whose probability is written in (8). As noted earlier, in my sample, the probability of abandoning IT—that is, choosing $y_{it} = 0$ after choosing $y_{i(t-1)} = 1$—is certain an equal to zero. This result makes it unattractive to consider (3) as a plausible specification.[5] Therefore, I shall be concerned only with the probability of adopting IT conditional on the state of not having it in place in the past. Thus, my main specification is reduced to:

$$y_{it} = \mathbf{1}(\eta_i + x'_{it}\beta + \varepsilon_{it} \geq 0). \tag{9}$$

One problem related to the sample design remains in the latter setup. As individual effects are constant across time, they perfectly predict the event $y_{it} = 0$ in the whole time dimension. That is, countries that choose always not to follow the IT regime (NITers for short, as opposed to ITers) do not contribute to the analysis.

Next I discuss key issues related to the panel data estimation of (9) which are not addressed by the existing empirical literature on the choice of IT regimes. The list of these issues follows: the asymptotic plan, the time series properties of x_{it}, the distribution function assumed for ε_{it}, and the challenges imposed by possible feedback from the choice of IT on the performance of the right-hand-side variables.

Information available at the individual level (i.e., people, families, firms, banks and so forth) for more than one period has spurred the development of the panel data methodology in the last thirty years. In this econometric context, typically, the number of individuals N is larger than the time dimension T. This explains why the theory of panel data regarding asymptotic results is prolific when assuming $N \to \infty$ and T fixed.

By asymptotic plan I mean to the inference the researcher makes about the large sample properties of data based on the dimensions of the sample available at hand. If N is much larger than T, the common asymptotic plan used in the microeconometric literature holds. Likewise, if both dimensions of the panel are large, the most amenable assumption is both N and $T \to \infty$.

The discussion outlined above is important because the asymptotic plan suggests the choice of the econometric method. When N is large compared to T, the researcher faces the incidental

[5] Technically speaking, this Markov chain is said to be reducible because one of the states (that of choosing IT in the previous period) is absorbing.

parameters problem in the estimation of a model like (9). This concept, owing to Neyman and Scott (1948), states that the estimation of a large number of individual effects compromises the consistency of the rest of the parameters.[6] Indeed, the literature on fixed and random effects estimators arise as a consequence of this contribution. The fixed effects estimator removes the individual effects; the second one estimates the common distribution of the exogenous variables and the individual effects applying simulation-based econometric methods.[7]

I design my country sample invoking an asymptotic plan that holds for N fixed and T large. Although I know that the MLE is consistent if $N \to \infty$ and T fixed or $T \to \infty$, the Monte Carlo experiments (reported in the Appendix) show that the bias is bearable when T is large and N is let to be fixed at 25 or 30.

Second, MLE, which is the estimator I shall use, rests on the basic assumption of stationarity for the exogenous variables. But in macroeconomic studies, like the one attempted here, it is possible for x_{it} to adopt the properties of non-stationary processes. For integrated processes of x_{it} in the context of discrete choice models, Park and Phillips (2000) show that parameter estimators have dual rates of convergence, which seems to be a novel finding in the econometric literature. This means that the MLE estimator, under uncertain conditions, can converge to the true value at two rates, one of which is faster than the other.[8] Obviously, in such a setup, the asymptotic theory becomes unreliable, giving some room in this paper for applying bootstrap techniques. Moreover, as I am uncertain about the consequences of departures from that distribution assumption, I carry out a variety of Monte Carlo experiments regarding different choices for the dimension of the panel data and the time series properties of an artificially generated independent variable x_{it} (see the Appendix).

Third, to estimate model (9) parametrically, researchers should make an assumption about the functional form of $\mathcal{F}$, that is, the distribution function followed by ε_{it}. It is a well known result in the econometric literature that a mistakenly assumed distribution function for errors renders parameter estimates inconsistent. Manski (1975) and Manski (1985) develop the maximum score estimator that is unrestricted in this regard. One disadvantage, however, is that the likelihood function is discrete (it is a step function) at the model parameters, making it difficult to derive its asymptotic distribution, although its consistency was earlier studied by Manski

[6] The individual effects are the incidental parameters.

[7] For the fixed effects estimator see Andersen (1970), Chamberlain (1980) and Honoré and Kyriazidou (2003). This latter paper extends the Andersen (1970)'s methodology, called the Conditional Logit Estimator, for dynamic panel data models. For the techniques used in the estimation of random effects models, see Gouriéroux and Monfort (2002). For a detailed survey of non-linear discrete choice models see Arellano and Honoré (2001) and Arellano (2003).

[8] Guerre and Moon (2002) show, for instance, that when the true value of the parameter is zero, the asymptotic normality distribution still holds.

(1985). Horowitz (1992) works in the smoothed version of Manski's estimator borrowing ideas from the literature of density estimation. As it happens in that literature, the performance of Horowitz's estimator is sensitive to the choice of the bandwidth. In particular, its asymptotic distribution depends on this parameter.

Early trails using this estimator convinced me that it has low convergence, specially in this framework in which I jointly estimate β and η_i. The strategy I take as a remedy consists in assuming various functional forms for the error distribution. I shall use the Logistic and Normal distributions yielding the so-called logit and probit models.

Finally, another basic assumption with regard to x_{it} is their exogeneity with respect to the dependent variable. Inflation Targeting is a monetary regime supported by a stable macroeconomic climate and a highly credible central bank, but in turn it also reinforces credibility and some macroeconomic conditions. For instance, after the adoption of IT, the success in guiding private expectations and attaining inflation targets can be the natural explanation for achieving *ex-post* low inflation rates—an assertion that indeed is supported by ample empirical evidence, see Corbo et al. (2002), Mishkin and Schmidt-Hebbel (2002), Schmidt-Hebbel and Werner (2002), and Mishkin and Schmidt-Hebbel (2007), among others. In fiscal matters, government could foster policies that guarantee a sustainable and careful management of fiscal accounts since under IT the central bank's discretionary lending is no longer available.

In presence of predetermined variables (including the lagged term of the dependent variable, so including model (3)), Arellano and Carrasco (2003) is a promising first step in the development of strategies—based on the generalized use of instrumental variables—to deal with endogeneity. In this paper, I use, instead, a pragmatic approach, using the first lagged terms of my (5 years-averaged) right-hand-side variables, which is a usual remedy found in the empirical literature.[9] The choice of 5 years for computing the averages is arbitrary but is intended to make clear that the choice of a regime is conceived as a long-run decision involving a long period of evaluation.

3 Empirical model

In this section I give equation (9) a concrete form. To define the values for y_{it}, I need information about the dates of IT adoption. I have used official information found in central banks' web pages. When this date is not reported explicitly I follow the dates used in previous papers.[10] $x_{it} = [INF_{it}\, BGT_{it}\, FIN_{it}\, GDP_{it}\, TOP_{it}]'$, where the capitalized words stand for inflation rate,

[9] Obviously, in an empirical setup such as the one developed here, it is impossible to control for endogeneity engendered by a rational expectation reasoning.

[10] See table 3 for alternative adoption dates.

government budget balance, financial development, GDP per capita, and trade openness.

A discussion on the expected signs for the estimated values of β follows. Perhaps, the first variable policymakers observe prior to adopting IT is the inflation rate. Masson et al. (1997) point out that a successful IT implementation needs a low-inflation environment. Although Chile and Israel challenge this claim, the general practice seems to first make some progress in inflation stabilization. Hence, I expect inflation rate to affect negatively the likelihood of choosing IT.[11] I expect the opposite for government budget balance, financial development and GDP per capita. Independent conduct of monetary policy, as another requisite, should be guaranteed by basic laws forbidding the provision of discretionary lending to the government and reducing the temptation of running bailouts in the financial system. Central banks lacking of this institutional capacity are said to be fiscally and financially dominated. Thus, a central bank suffering from fiscal or financial dominance or both is loath to choice IT. As central bank independence and credibility are clearly broad and qualitative concepts that are hard to measure, I shall rely on the GDP per capita as an overall indicator of institutional development because an index à la Cukierman (1992) with sufficient time variation is not available. Finally, I assume countries with high exposure to the best international practices on macroeconomic policies and structural reforms—measured by trade openness—to be prone to adopt IT.

I assemble data for ITers over the period 1975-2005.[12] In addition to the technical problem regarding the sample design pointed out in section 2, the inclusion of more countries in the estimation of (9) would be cumbersome for two reasons. First, as mentioned above, I want to restrict N to be as large as T because I desire estimates to become immune to the incidental parameters problem. Recall that in addition to β I also estimate η_i.[13] Second, my sample of ITers is already unbalanced—the choice of IT only represents 26%[14] of the observations of y_{it}. With the inclusion of more countries, that is, in a asymptotic plan with $N \to \infty$, the percentage of 1 in y_{it} tends to vanish—while the number of ITers remains fixed, the number of NITers becomes larger—thereby making inessential the estimation of (9).

I end this section with a complementary analysis of data in two respects. Commonly, overall economic development suggests that financial development, GDP per capita, and trade openness

[11] I use the normalized inflation rate, which is the rate of inflation divided by the latter variable plus 1. I use this definition in order to mitigate the influence of hyperinflation episodes. For details on the construction and definition of the rest of the variables, see table 4.

[12] See the list of countries in table 5.

[13] One additional gain of working under this setup (in which I estimate η_i) is that I can estimate marginal effects properly, that is, taking into account the individual heterogeneity.

[14] Discarding government budget balance, which is the most restrictive variable in number of observations, this percentage increases to 35%. Yet I take the risk of including that variable because of its key role in the IT adoption likelihood.

move together, implying that collinearity problems could arise. In table 6, I report pair-wise correlation coefficients for all the variables used in this study. I display calculations in two ways. On one hand, I apply this estimator over time-demeaned variables—getting cross-section correlations. On the other hand, I carry out the estimations taking the variables in levels and computing the whole panel (co)variation—obtaining pooled panel correlations. Four results emerge from that table. First, my dummy variable for the choice of IT is negatively correlated with the inflation rate, but positively correlated with the rest of the variables only when exploiting the whole variation. Second, the pair-wise correlations among financial development, GDP per capita, and trade openness are positive and significant whatever the way of computation. In order of magnitude, the correlation between financial development and GDP per capita comes first—with a moderate value, therefore not implying a chronic collinearity—followed by the correlation of the latter variable and trade openness. Third in the list is the correlation reported by financial development and trade openness. In addition, I look for some association between my indirect measures of fiscal and financial dominance. As expected, this association is positive and significant, although small in magnitude. This result, however, holds only in the panel dimension. Finally, the inflation rate is negatively related to the other variables, showing correlations that are low in magnitude and robust in significance to both dimensions.

With regard to the second issue, an absent exercise in the panel data empirical literature is the analysis of variance (ANOVA), by which the total variance is decomposed into variances calculated across time (*within* variance) and between individuals (*between* variance). The use of panel data models concerned with within variance—the so-called within estimator in linear models—implicitly assumes that source of variation is the most important. Thus, as a means of warranting the estimation strategy proposed here, in table 7 I report the ANOVA results for my right-hand-side variables. In this table, the high contribution of the between variance for financial development, GDP per capita and trade openness contrasts to the nearly balanced contribution in total variance for inflation rate and government budget balance. This picture shows that the choice among models focusing on any source of variation is not clear. Consequently, this finding reinforces the econometric strategy taken here in which I exploit the whole variation by estimating the individual effects.[15]

[15] Clearly, both the within and between transformations do not apply in non-linear models (e.g., discrete choice models). Honoré and Kyriazidou (2003) show, however, that the Conditional Logit Estimator, which is the fixed effects estimator in discrete choice models, admits a similar interpretation to the one assigned to the within estimator in linear models.

4 Results

Without an underlying theoretical model, it is difficult to justify what subset of the exogenous variables (conforming the best model) enters into equation (9). As mentioned above, I restrict the number of exogenous variables to five, including macroeconomic and institutional preconditions, and a structural variable. This set can be considered little. Only one variable included in the reviewed literature is not considered in this paper.[16] Hu (2006), for instance, uses data on exchange rate regimes constructed by Reinhart and Rogoff (2004) and Levy-Yeyati and Sturzenegger (2005) as measures of *de facto* central bank independence. One problem with this data, however, is that the classified observations related to hyperinflation periods and missing data on dual markets leave a small fraction of usable data in some countries.[17] As my sample of countries is already small, I prefer to discard this variable.

I estimate all possible models (i.e., $2^5 - 1$) resulting from combinations of these 5 variables. As I need a criterion to compare the performance of these models, I compute the Akaike, Schwarz and Hannan-Quinn information criteria.[18] Additionally, I calculate the Hochberg (1988)'s modified Bonferroni p-value bounds for testing multiple hypotheses that all individual parameter estimates (including individual effects) in each model are zero.

The values computed for the information criteria—displayed in tables 8 (logit) and 9 (probit)—reveals that there is consensus in selecting the best model, which includes all 5 variables (model 31 in the tables). The ordered p-value bounds, reported in table 10, show that all models except three of them, display multiple statistical significance.

The latter discussion means that when estimating marginal effects, which are the policy parameters of interest, I shall exploit various sources of the relevant information in shaping the likelihood of choosing IT.[19] Table 11 shows parameter estimates and their respective marginal

[16] Among the variables I consider as relevant. Shocks variables should not enter, in principle, in the set of possible explanatory variables because it is hard to believe that transitory events would drive the choice of a monetary regime, which entails, instead, a balance of benefits and cost in a long horizon.

[17] Reinhart and Rogoff (2004) classify these episodes separately.

[18] Recall that these criteria measure the ability of a model to maximize the probability of observing the data, accounting for the loss of degrees of freedom implied by the estimation of the model parameters. That is, they sum the contribution to the log-likelihood (a negative value) minus a penalized function that depends on the number of estimated parameters. That explains why researcher must select the model with the lowest value of these criteria. These statistics, however, differ in that unlike the Akaike criterion, the Schwarz and Hannan-Quinn criteria are consistent (they select the best model as T grows).

[19] This claim does not mean that β has no interpretation. Indeed, β is the log of the odds ratio, that is, it measures the influence of the exogenous variable on the likelihood of choosing IT relative to the alternative option.

effects for both the logit and probit estimations for my best model.[20] The calculation of the marginal effects is based on the traditional approach by which the expression of the marginal effect is evaluated at average values of the exogenous variables.[21] Before referring to the parameter estimates, note that I also test for the relevance of fixed effects using the statistics suggested by Baltagi (1995) and Gurmu (1996). The null hypothesis is that all fixed effects are zero (i.e., that the true model is a pooled panel model which neglects country heterogeneity). In the four sets of results—resulting from different specifications and error distributions—discussed below, it is possible to reject the null, and therefore, validate the model exposed in equation (9).

Next I discuss my baseline results. As expected, both macroeconomic and institutional preconditions are highly significant; although, fiscal position is the exception. It is not fair to consider this latter result as puzzling because I have not developed a theoretical model, but it is counterintuitive. Recall that government budget balance is troublesome because of its availability. Therefore, this result could be the consequence of this fact. Inflation rate, financial development, and GDP per capita show the expected signs; and not only the log of odds ratios are significant but also the marginal effects calculated as discussed above.[22] Note that these results are also robust to the distribution assumed for errors.

Alternatively, table 11 also presents robustness checking results by dropping government budget balance from the main specification. Main results remain and indeed the significance of some of the marginal effects—those for trade openness and GDP per capita—improves, although all of them lose numerical magnitude when assuming logistic errors. In the probit regressions the same occurs, except for trade openness and GDP per capita.

Recent empirical findings in this regard show that the latter results, regarding sign contribution and statistical significance, are robust to alternative econometric methods (i.e., the so-called fixed and random effects estimators).[23]

Numerically, the inflation rate has the highest impact on the likelihood of choosing IT, followed by trade openness, financial development, and GDP per capita. This assertion, however, is misleading. For interpreting properly the marginal contribution of these variables, I do some back-of-the-envelope calculations only for the baseline logit regression, which I report in table 12. The marginal effects are not directly comparable. For instance, a 10% reduction in inflation

[20] I tried to estimate these regressions including time effects but without success because of numerical problems.

[21] As is well known, another method consists in averaging individual marginal effects computed for each individual (country).

[22] p-values are robust to misspecification. This means that however you assume the incorrect error distribution, the significance of the parameter estimates still holds, see White (1982). The standard errors for the marginal effects were calculated using the Delta method. Note that the marginal effect estimator is consistent only when $T \to \infty$ (Carro (2007)), an assumption that holds in this paper.

[23] See Calderón and Schmidt-Hebbel (2008).

does not amount to an increase in financial development of 10% because each change demands different efforts from an economic policy view. But I can rest on some stylized facts for making these results more comprehensible. Hence, a reduction in the inflation rate from 17% to 5%—a similar course followed by the Chilean inflation during the 1990s—increase the probability of adopting IT by 13%, which is not a meaningless figure if considering other factors. Moreover, the impact of an increase in the log of GDP per capita by 1.2 seems huge (65.64%), but if taking into account that this increase accounts for a transition between income categories (from lower-middle to upper-middle income), it is not surprising. Finally, an increase in trade openness and financial development by 10 percentage points has a relatively low impact on the likelihood of choosing IT.

As I said before, my right-hand-side variables are the 5-year-based averages of the variables discussed above. This choice is arbitrary and for that reason I also estimate the baseline and alternative regressions using averages based on 3, 4, 6 and 7 years, in tables 13, 14, 15 and 16, respectively. Two results arise from this exercise. First, interestingly, the numerical magnitude of marginal effects changes in different directions among variables as moving from the regression that uses the shortest period (3 years) for the estimation of the average values to the regression using the longest period (7 years). Thus, in logit regressions the marginal contribution to the likelihood of IT adoption decreases for inflation rate and GDP per capita, while the opposite applies for budget balance and financial development. In the probit regressions, this nearly monotonic relationship is weak only for GDP per capita. Second, the significance and sign of the estimated parameter value associated to budget balance converge to what I expected as a result of considering more years in the calculation of the averages. In particular, in 7-year-based estimations, this variable is significant (although at 10% of significance) and accompanied by the expected sign.

Obviously, the numerical values for the log of odds ratios and the marginal effects differ across tables—because a 3-year-based variable is qualitatively different from a 7-year-based variable—and this should not be interpreted as a lack of robustness.

As an another robustness check I tried to estimate both specifications—with and without government budget balance—using alternative dates of IT adoption (corresponding to the stationary (ST) and fully-fledged (FF) periods), shown in table 3, but without success. Specifically, I encountered numerical problems probably arising from a fairly unbalanced dependent variable. That is, with the alternative dates the percentage of number 1 in y_{it} declines to 18% (25%) and 22% (30%), respectively, including (dropping) government budget balance.

Now let me come back to the discussion on marginal effects. I said that their estimation follows the traditional approach. Nevertheless, this method rests on the assumption that the distribution of marginal effects has a symmetric behavior and one mode. The use of the median instead of the mean could arise as a solution for the first issue; but the second issue is more difficult to deal with. To overcome the shortcomings associated to representative statistics, I estimate the sample density of the marginal effects. As in figure 2, I display in figure 3 the cross-country distribution of the marginal effects computed in the pre-period, the starting date, and the post-period.[24] Also, I show the associated predicted probabilities of adopting IT across time and for each country in figures 4-7.

Cross-country distributions in the pre-period (see the blue lines) try to mimic the shape of the distribution estimated in the date of adoption as moving across the horizon. Note that even this distribution is asymmetric (right biased) as shown by the green line. Then, post-period distributions show an asymmetric shape like the one exhibited by pre-period distributions. This result is consistent with what I expected a priori given the trending behavior of the majority of my right-hand-side variables. Marginal contributions to the likelihood of choosing IT should increase before the starting date while they should decrease during the post-period. Once countries adopt IT, marginal effects of the key macroeconomic and institutional preconditions, found relevant empirically in this paper, should be lower—because there is no gain in practice, other than benefits stemming from reinforcing the regime.

In sum, although the traditional approach for computing marginal effects is readily available, it tends to hide interesting issues about the whole distribution of them. Thus, we have seen that the preconditions' contribution to the probability of adopting IT is quite heterogenous among countries and across periods, before and after the adoption date. Although the typical problem of sample size in density estimation applies in this case (recall that I have 25 countries), these results are congruent with the relevance of initial conditions—in contrast with findings of Batini and Laxton (2007)—at the moment of the adoption, as reflected by a different exposure of countries to the likelihood of choosing IT.

5 Conclusions

The inflation targeting regime has become the monetary policy framework of choice in many industrial and developing countries. Currently, 28 countries follows this regime. Based on these experiences it would be informative to know what are the main preconditions they have observed before adopting a monetary regime based on the announcement of inflation targets. This is not an easy task because the empirical literature and the monetary policy practice have shown that countries differ in their initial conditions at the time of IT adoption.

[24] Marginal effect of the variable k is computed as $\hat{\beta}_k \widehat{\mathcal{F}}(1-\widehat{\mathcal{F}})$, where $\widehat{\mathcal{F}}$ is the logistic cumulative distribution function evaluated at the estimated parameter values and $\hat{\beta}_k$ is the associated parameter estimate of variable k. I report only $\widehat{\mathcal{F}}(1-\widehat{\mathcal{F}})$ because this expression is sufficient for shaping the distribution of marginal effects.

The main focus of this paper is to study empirically the main determinants that drive the choice of IT. By using a novel empirical approach—among those found in the existing literature on IT regimes—I find that financial development, GDP per capita (as a measure of overall economic development) and trade openness exert a positive contribution to the likelihood of adopting IT. The inflation rate affects such a likelihood negatively. These results are robust to different specifications and alternative definitions of the right-hand-side variables. Also, note that these results are only valid for comparing ITer experiences before and after the IT adoption. They do not generalize to any NITer.

One issue that is currently at debate is the relevance of the initial conditions at the time of IT adoption. In contrast to Batini and Laxton (2007), my results suggest that the initial conditions do matter because countries have a different exposure to the likelihood of choosing IT as a result of their macroeconomic and institutional fundamentals and unobservable idiosyncratic factors, possibly correlated with the first ones.

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6 Appendix

6.1 Monte Carlo Study

I perform Monte Carlo experiments for studying the large sample properties of the MLE regarding two issues: the size of the panel data and the time series properties of the exogenous variables. I focus on the first issue because the cross-section dimension of my sample is not so long as the one typically employed in the microeconometric literature. My sample comprises only 25 countries. In addition, because I use macroeconomic time series, T is large compared with the time dimension usually available in microdata. The second kind of exercises assesses the role of different forms of time dependence and tries to broaden the scope of the simulation results reported in Park and Phillips (2000), which are restricted to cross-section regressions.

Consider again the model exposed in (9). I generate 1000 artificial series for the dependent variable making some assumptions about the distribution followed by 1000 artificial series for x_{it} and the stochastic error term, ε_{it}. In the experiments undertaken here, I assume the above mentioned error term is distributed logistically.[25] For x_{it}, which is a scalar, I consider six cases:

Case 1:	$x_t = u_t, \quad u_t \sim \mathcal{N}(0, \pi^2/3)$
Case 2:	$x_t = 0.10 + 0.90x_{t-1} + u_t, \quad u_t \sim \mathcal{N}(0, 1)$
Case 3:	$x_t = 0.10 + 0.99x_{t-1} + u_t, \quad u_t \sim \mathcal{N}(0, 1)$
Case 4:	$x_t = x_{t-1} + u_t, \quad u_t \sim \mathcal{N}(0, 1)$
Case 5:	$x_t = 0.5 + x_{t-1} + u_t, \quad u_t \sim \mathcal{N}(0, 1)$
Case 6:	$x_t = 0.25t + 0.1x_{t-1} + u_t, \quad u_t \sim \mathcal{N}(0, 1)$

where, u_t is a stochastic term. Also, I allow for correlation between individual effects and the exogenous variable by defining $\eta_i = T^{-1}\sum_{t=1}^{T} x_{it}$ as in Carro (2007). MLE contemplates cases 1 to 3, in which x_{it} distributes normally, and follows a persistent and highly persistent autoregressive process. In addition, x_{it} is set to follow a random walk process without drift (case 4) and with drift (case 5). Park and Phillips (2000) study case 4 but in a cross-section framework, showing in a multiple variable setting that the parameter estimators have dual rates of convergence. The inclusion of the sixth case, in which x_{it} is modeled as a trend stationary process, gives completeness. Regarding the panel data dimensions, N and T are set equal to $\{25\,,30\,,50\}$ and $\{10\,,20\,,30\,,40\,,50\}$, respectively. The choice of the parameters in cases 1–6 tries to mimic the time series behavior of my exogenous variables.

[25] Simulations assuming normally distributed errors were not performed because of time limitations.

Table 1 and table 2 report the results of the experiments regarding percentage bias (PB) and root mean squared error (RMSE). The PB is measured as the bias divided by the true parameter's value while the RMSE is the root of the sum of variance and squared bias. The first table shows that, in general, the PB of the MLE becomes acceptable as both N and T grow (about 3% when $N = T = 50$). The same occurs for the efficiency of the estimator (see table 2). I shall focus my attention on table 1. By comparing cases 1, 2 and 3, you see the PB is greater when x_{it} follows a highly persistence stationary process. A similar conclusion arises from the comparison of cases 3 and 4; however, in some experiments they tend to exhibit a similar behavior. Also, the inclusion of drift in the random walk process increases the PB. As yet, these findings are linked with those reported by Park and Phillips (2000) in matters of rate of convergence. I show in addition that when x_{it} is assumed to be a trend stationary process, the asymptotic properties of MLE are better than those displayed by the random walk processes but worse than those exhibited by the stationary processes. Curiously, the latter relationship breaks down when $T = 30$, as revealed by the comparison between cases 5 and 6, probably reflecting the need for more simulations.[26] Moreover, you note that PB does not decrease monotonically as N grows, contradicting what might be expected. Again, N in this paper is much smaller than the number of individuals found in microeconomic surveys. Hence, it is possible that the range of values for N considered here were not sufficient for generating more conclusive results in this regard.

The interesting result, however, is that there is more gain in bias reduction when T grows than when N grows (compare the results for N, T=$\{30, 50\}$, see also figure 1). Recall that my panel data's dimensions are unusual from the perspective of the microeconomic literature. Although I assume that N is fixed, the message of these experiments is that I can rest on the gains in bias reduction provided by the time dimension.

[26]Note, however, that the cross-section dimensions considered here are far from being similar to those typically employed in the microeconomic literature (e.g., $N = 500$).

Table 1: **Monte Carlo Results: Percentage Bias (%)**

Maximun Likelihood Estimation
$y_{it} = \mathbf{1}(\eta_i + x_{it}'\beta + \varepsilon_{it} \geq 0)$
$\beta = -1, \eta_i = (1/T)\sum_{t=1}^{T} x_t$
Note: $u_t \sim \mathcal{N}(0,1)$, except where otherwise stated
Number of experiments=1000

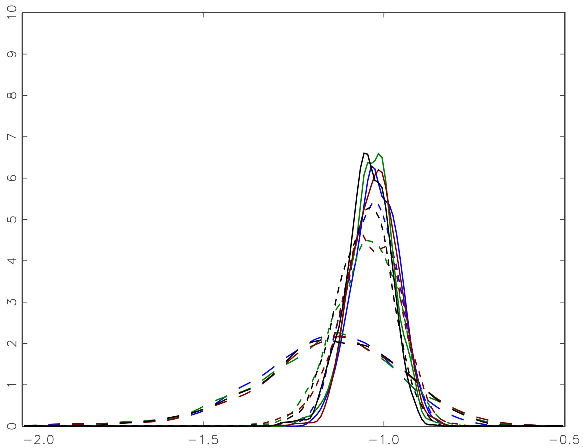
	$T = 10$	$T = 20$	$T = 30$	$T = 40$	$T = 50$
Case 1: $x_t \sim \mathcal{N}(0, \pi^2/3)$					
$N = 25$	17.45	7.16	4.32	3.46	2.22
$N = 30$	16.39	6.73	4.10	3.24	2.55
$N = 50$	14.87	6.98	4.34	3.19	2.48
Case 2: $x_t = 0.1 + 0.90x_{t-1} + u_t$					
$N = 25$	14.61	6.65	4.28	3.39	2.54
$N = 30$	14.12	6.74	4.15	3.63	2.66
$N = 50$	12.81	6.69	4.54	3.14	2.61
Case 3: $x_t = 0.1 + 0.99x_{t-1} + u_t$					
$N = 25$	16.16	7.34	4.64	3.94	3.31
$N = 30$	14.63	7.12	4.70	4.05	3.60
$N = 50$	13.63	7.67	5.09	3.89	3.28
Case 4: $x_t = x_{t-1} + u_t$					
$N = 25$	16.34	7.59	4.99	3.92	3.35
$N = 30$	14.59	7.27	5.04	4.28	3.68
$N = 50$	13.86	7.66	5.30	4.14	3.36
Case 5: $x_t = 0.5 + x_{t-1} + u_t$					
$N = 25$	16.35	7.62	4.88	4.23	3.79
$N = 30$	15.01	7.57	4.92	4.19	3.65
$N = 50$	13.77	7.73	5.41	4.23	3.45
Case 6: $x_t = 0.25t + 0.1x_{t-1} + u_t$					
$N = 25$	15.32	6.31	5.59	4.93	4.58
$N = 30$	14.87	6.87	5.77	4.84	4.54
$N = 50$	13.02	6.84	5.38	4.80	4.25

Table 2: **Monte Carlo Results: Root Mean Squared Error**

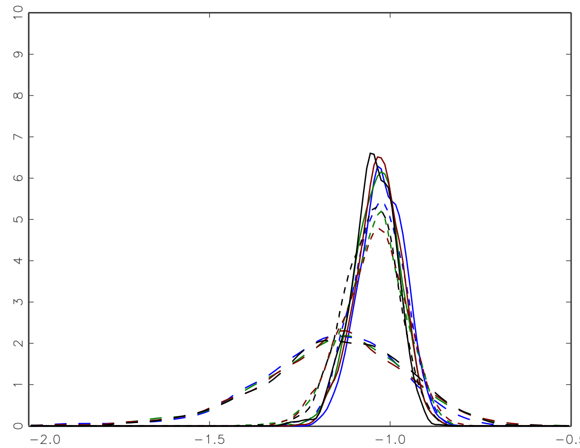
Maximun Likelihood Estimation
$y_{it} = \mathbf{1}(\eta_i + x'_{it}\beta + \varepsilon_{it} \geq 0)$
$\beta = -1, \eta_i = (1/T)\sum_{t=1}^{T} x_t$
Note: $u_t \sim \mathcal{N}(0,1)$, except where otherwise stated
Number of experiments=1000

	$T=10$	$T=20$	$T=30$	$T=40$	$T=50$
Case 1: $x_t \sim \mathcal{N}(0,\pi^2/3)$					
$N=25$	0.26	0.13	0.09	0.08	0.07
$N=30$	0.23	0.12	0.08	0.07	0.06
$N=50$	0.19	0.10	0.07	0.06	0.05
Case 2: $x_t = 0.1 + 0.90x_{t-1} + u_t$					
$N=25$	0.25	0.13	0.09	0.08	0.07
$N=30$	0.23	0.12	0.09	0.07	0.06
$N=50$	0.19	0.10	0.08	0.06	0.05
Case 3: $x_t = 0.1 + 0.99x_{t-1} + u_t$					
$N=25$	0.26	0.13	0.10	0.08	0.07
$N=30$	0.23	0.12	0.09	0.07	0.07
$N=50$	0.19	0.11	0.08	0.06	0.06
Case 4: $x_t = x_{t-1} + u_t$					
$N=25$	0.26	0.13	0.10	0.08	0.07
$N=30$	0.23	0.12	0.09	0.08	0.07
$N=50$	0.20	0.11	0.08	0.07	0.06
Case 5: $x_t = 0.5 + x_{t-1} + u_t$					
$N=25$	0.26	0.13	0.10	0.08	0.07
$N=30$	0.23	0.12	0.09	0.08	0.07
$N=50$	0.20	0.11	0.08	0.06	0.06
Case 6: $x_t = 0.25t + 0.1x_{t-1} + u_t$					
$N=25$	0.25	0.12	0.09	0.09	0.08
$N=30$	0.23	0.11	0.09	0.08	0.07
$N=50$	0.18	0.10	0.08	0.07	0.06

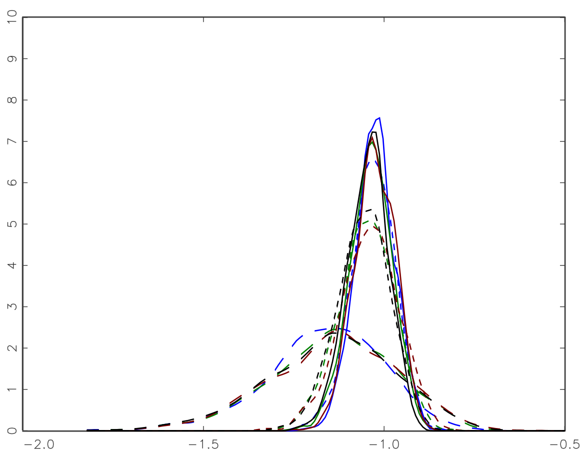
Figure 1: **Monte Carlo Results: Distribution of β**



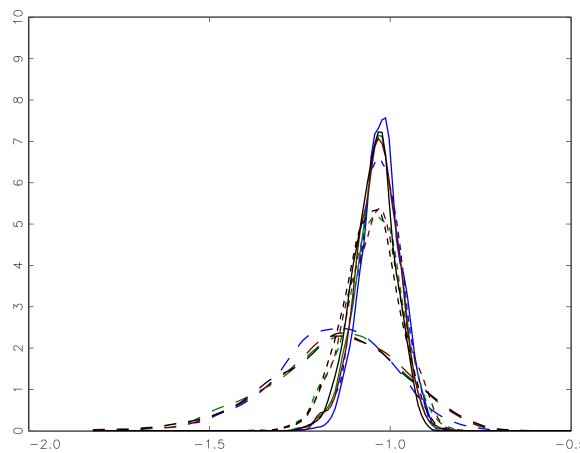
$N = 25, T = \{25, 50\}$: cases 1,2,4 and 6



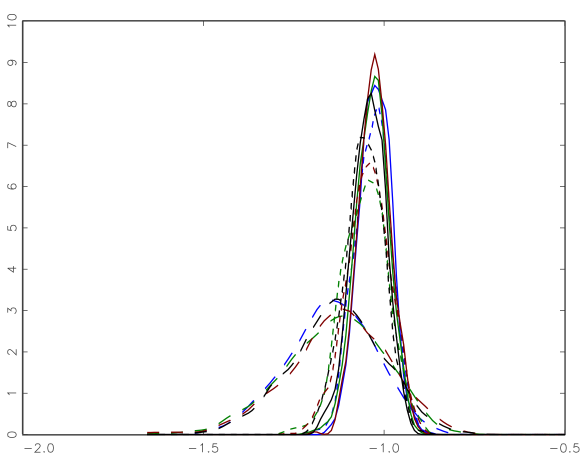
$N = 25, T = \{25, 50\}$: cases 1,3,5 and 6



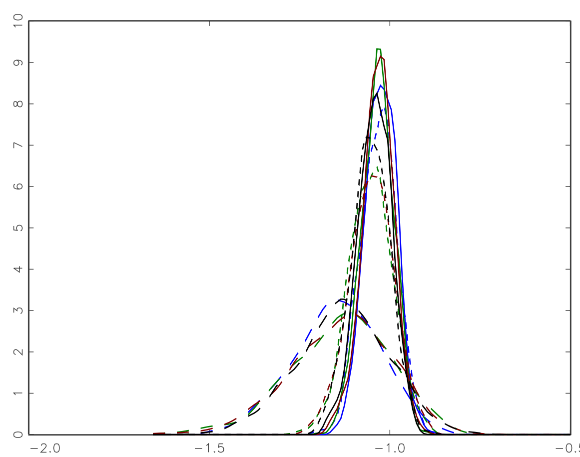
$N = 30, T = \{25, 50\}$: cases 1,2,4 and 6



$N = 30, T = \{25, 50\}$: cases 1,3,5 and 6

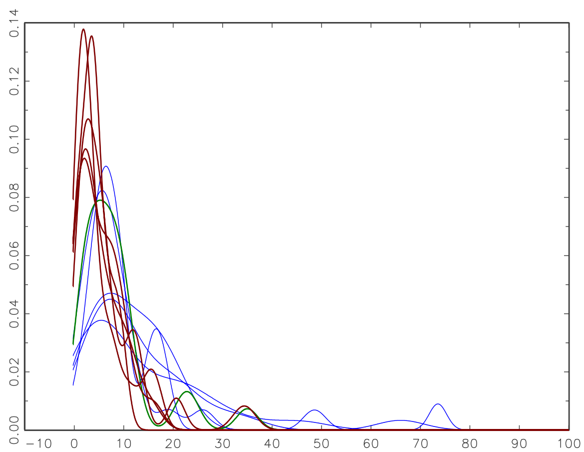


$N = 50, T = \{25, 50\}$: cases 1,2,4 and 6

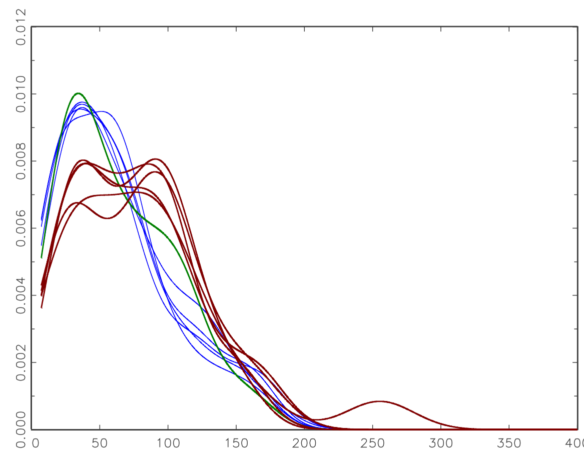


$N = 50, T = \{25, 50\}$: cases 1,3,5 and 6

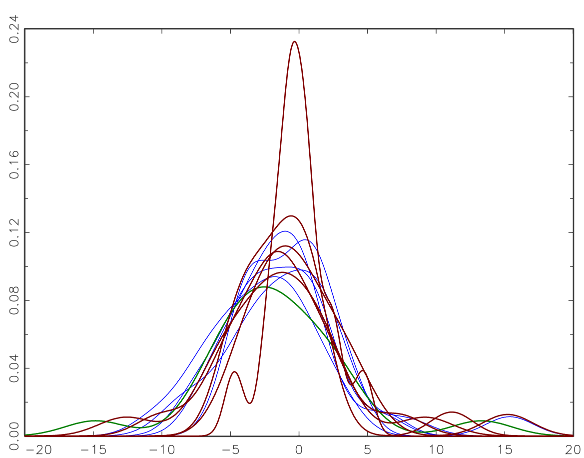
Figure 2: **Cross-country Distribution of Key Macroeconomic and Institutional Preconditions for Adopting IT**



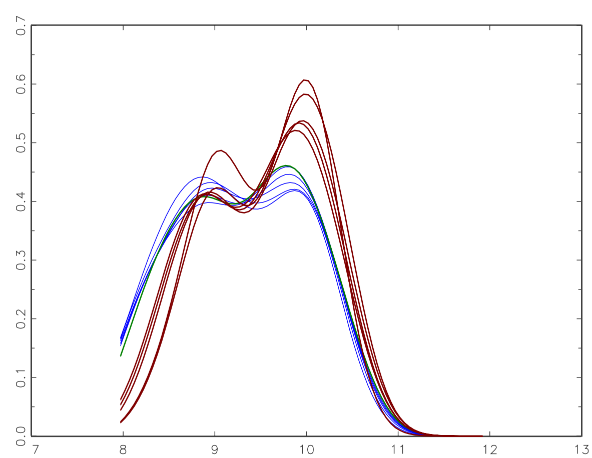
Cross-country distribution in $\{t-5,\dots,t+5\}$ for inflation



Cross-country distribution in $\{t-5,\dots,t+5\}$ for financial development



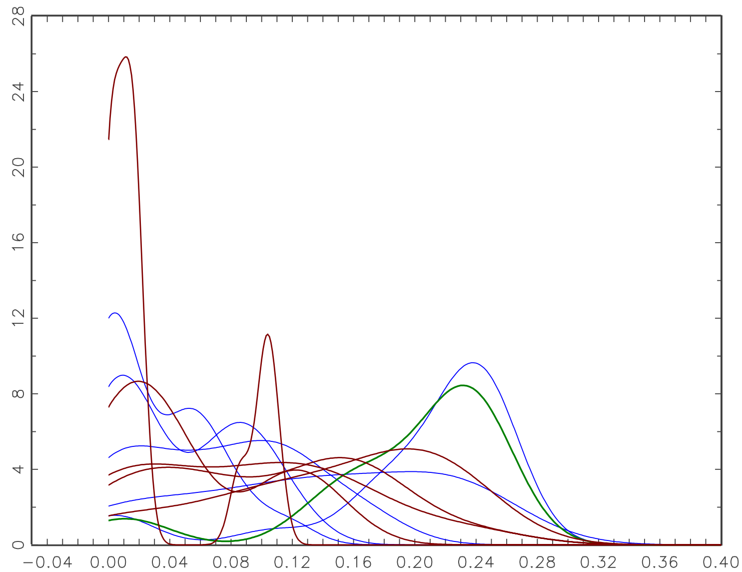
Cross-country distribution in $\{t-5,\dots,t+5\}$ for government budget balance



Cross-country distribution in $\{t-5,\dots,t+5\}$ for (log of) GDP per capita

Cross-country distributions for $\{t-5,\dots,t-1\}$, t, $\{t+1,\dots,t+5\}$ in blue (5 years), green (1 year) and red (5 years), respectively. Horizontal axis: the range of values of the variable, vertical axis: values of the density function estimated using the Gaussian kernel.

Figure 3: **Cross-country Distribution of** $\widehat{\mathcal{F}}(1-\widehat{\mathcal{F}})$



Cross-country distributions for $\{t-5,\dots,t-1\}$, t, $\{t+1,\dots,t+5\}$ in blue (5 years), green (1 year) and red (5 years), respectively. Horizontal axis: the range of values of the variable, vertical axis: values of the density function estimated using the Gaussian kernel.

Figure 4: **Predicted Probabilities $(\widehat{F})$ of Adopting IT for each Country**

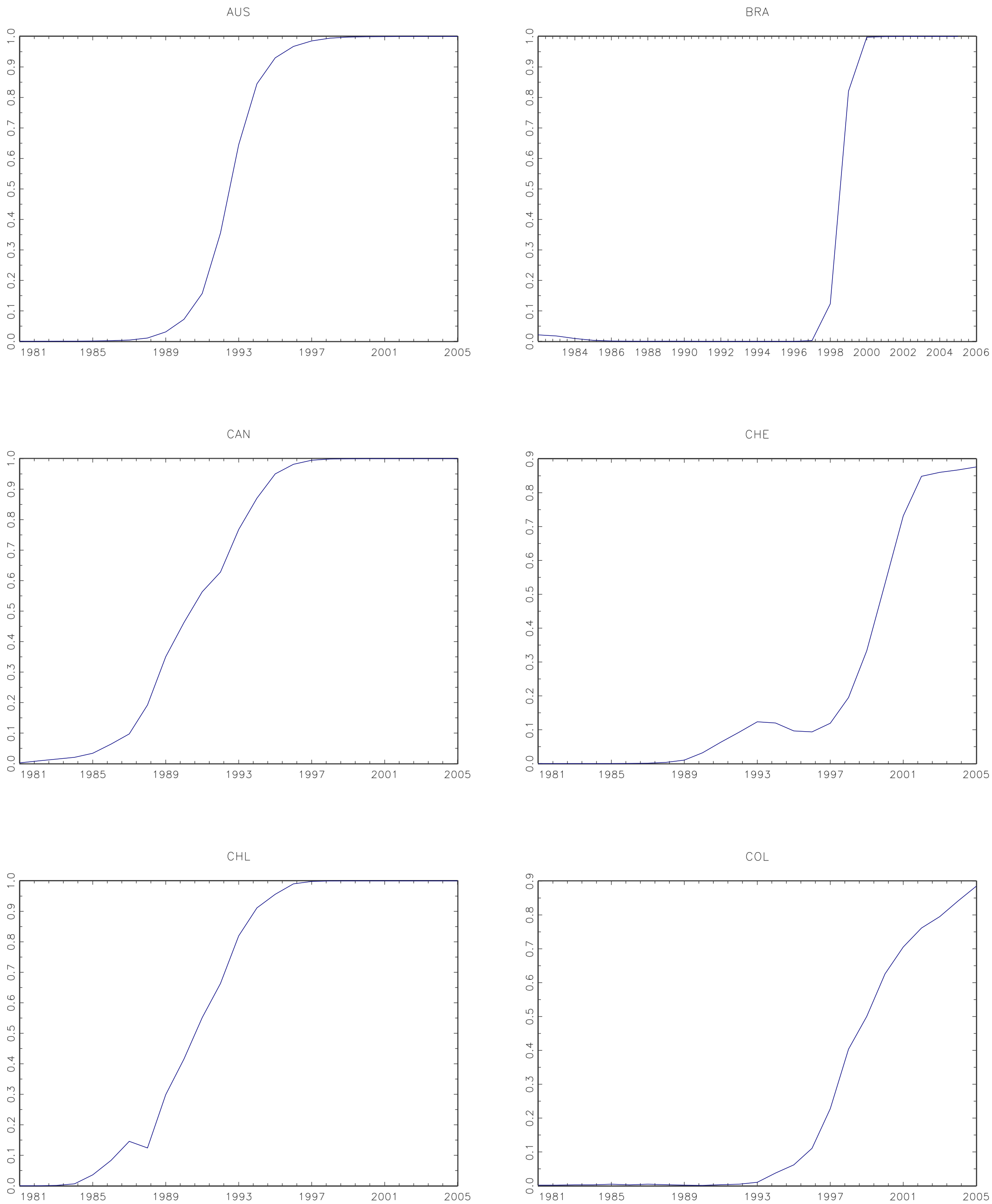


Figure 5: **Predicted Probabilities $(\widehat{F})$ of Adopting IT for each Country (continued)**

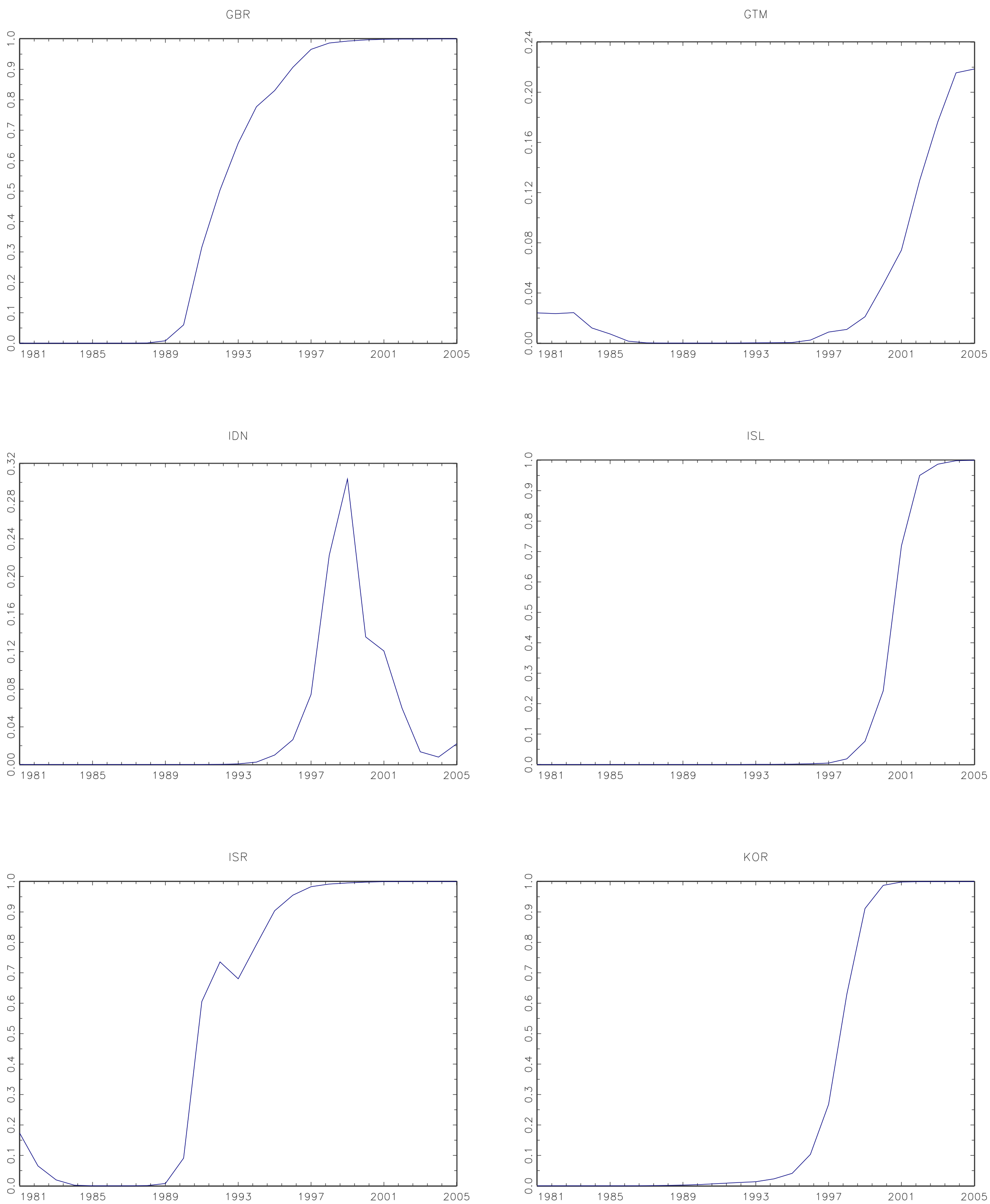


Figure 6: **Predicted Probabilities $\left(\widehat{F}\right)$ of Adopting IT for each Country**

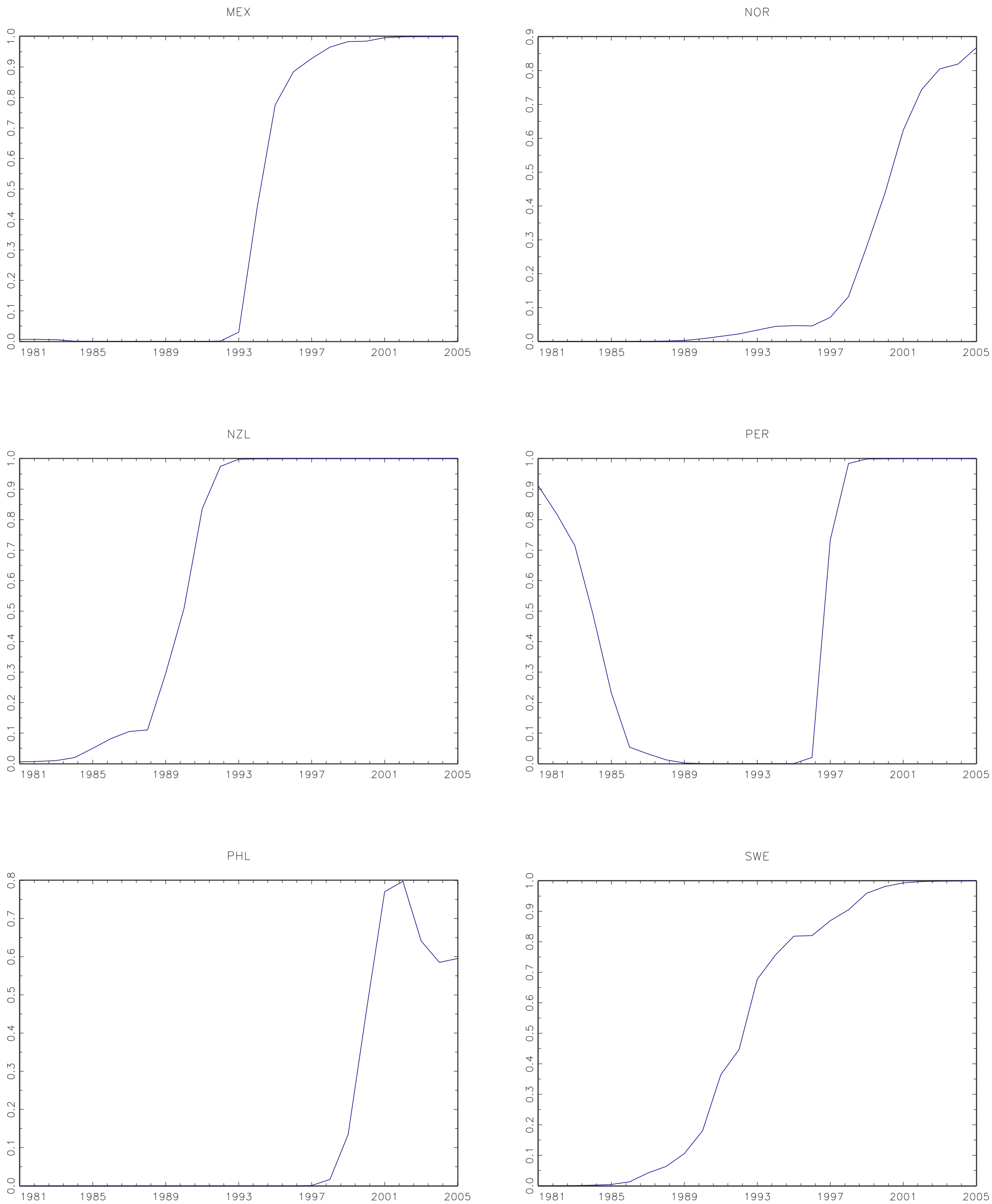


Figure 7: **Predicted Probabilities $\left(\widehat{F}\right)$ of Adopting IT for each Country (concluded)**

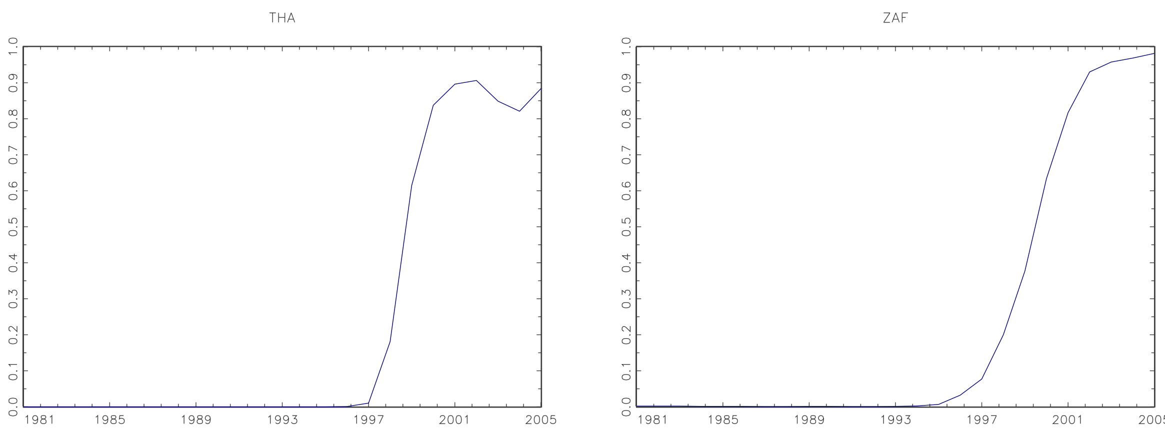


Table 3: **Starting Dates of IT 2005 according to Different Sources**

	(1) Corbo *et. al* (2001)	(2) Fracasso *et. al* (2003)	(3) Fraga *et. al* (2003)	(4) Levin *et. al* (2004)	(5) Pétursson (2004)	(6) Ball and Sheridan (2005)	(7) Schaech–ter *et. al* (2000)	(8) Truman (2003)	(9) Bernanke *et. al* (1999)	(10) Central Bank web pages	(11) IT Adoption dates used here (11a) PP or FF	(11b) FF	(11c) ST	(12) 2005 inflation target level (%)
AUS	1994	Sep–1994	Apr–1993	1993	Apr–1993	Q4–1994	Jun–1993	Jun–1993	Sep–1994	1993	1993	1993	1994	2–3
BRA	1999	Jun–1999	Jun–1999	Jun–1999	Jun–1999	–	Jun–1999	Jun–1999	–	Jun–1999	1999	1999	–	4.5 (+/-2.5)
CAN	1991	Feb–1991	Feb–1991	1991	Feb–1991	Q1–92(4)	Feb–1991	Feb–1991	Feb–1991	Feb–1991	1991	1991	1995	1–3
CHL	1991	Jan–1991	Jan–1991	Jan–1991	Sep–1990	–	Sep–1999	Sep–91/99	–	Sep–1990	1991	2000	2001	2–4
COL	1999	Sep–1999	Sep–1999	Sep–1999	Sep–1999	–	–	Oct–1999	–	1999	2000	2000	–	5 (+/-0.5)
CZE	1998	Jan–1998	Jan–1998	Jan–1998	Jan–1998	–	Dec–1997	Dec–1997	–	Jan–1998	1998	1998	–	3 (+/-1)
GTM	–	–	–	–	–	–	–	–	–	Jan–2005	2005	2005	–	4–6
HUN	–	Jul–2001	Jun–2001	Aug–2001	Jan–2001	–	–	Jun–2001	–	Jun–2001	2001	2001	–	3.5 (+/-1)
ISL	2001	Mar–2001	Mar–2001	–	Mar–2001	–	–	Mar–2001	–	Mar–2001	2001	2001	2003	2.5
IDN	–	–	–	–	–	–	–	–	–	Q1–2005	2005	2005	–	6.0 (+/-1)
ISR	1992	Jan–1992	Jan–1992	Jan–1992	Jan–1992	–	Jun–1997	Dec/Jun–91/97	Jan–1992	–	1992	1997	2003	1–3
MEX	1999	Jan–1999	Jan–1999	Jan–1999	Jan–1999	–	–	Jan–95/01	–	Jan–2001	1995	2001	2003	3 (+/-1)
NZL	1990	Apr–1988	Mar–1990	1990	Mar–1990	Q3–90(3)	Jul–1989	Dec–1989	Mar–1990	–	1990	1990	1993	1–3
NOR	2001	Mar–2001	Mar–2001	2000	Mar–2001	–	–	Mar–2001	–	Mar–2001	2001	2001	2001	2.5
PER	1994	Jan–2002	Jan–1994	Jan–2002	Jan–2002	–	–	Jan–2002	–	Jan–2002	1994	2002	2002	2.5 (+/-1)
PHL	–	Jan–2002	–	Jan–2002	Jan–2002	–	–	Jan–2002	–	Jan–2002	2002	2002	–	5–6
POL	1998	Oct–1998	Oct–1998	Jun–1998	Oct–1998	–	Mar–1999	Sep–1998	–	Sep–1998	1999	1999	2004	2.5 (+/-1)
ROM	–	–	–	–	–	–	–	–	–	Aug–2005	2005	2005	–	7.5 (+/-1)
SVK	–	–	–	–	–	–	–	–	–	Q1– 2005	2005	2005	–	3.5 (+/-0.5)
ZAF	2000	Feb–2000	Feb–2000	Feb–2000	Feb–2000	–	Feb–2000	Feb–2000	–	Feb–2000	2000	2000	2001	3–6
KOR	1998	Apr–1998	Jan–1998	Apr–1998	Apr–1998	–	–	Apr–1998	–	Apr–1998	1998	1998	1999	2.5–3.5
SWE	1993	Jan–1993	Jan–1993	1995	Jan–1993	Q1–1995	Jan–1993	Jan–1993	Jan–1993	1993	1993	1993	1995	2 (+/-1)
CHE	2000	Jan–2000	Jan–2000	2001	Jan–2000	–	–	–	–	–	2000	2000	2000	0–2
THA	2000	May–2000	Apr–2000	May–2000	May–2000	–	–	May–2000	–	May–2000	2000	2000	2000	0–3.5
GBR	1992	Oct–1992	Oct–1992	1992	Oct–1992	Q1–1993	Oct–1992	Oct–1992	Oct–1992	Oct–1992	1993	1993	1993	2

Notes

(1) They follow Schaechter, Stone and Zelmer in classifying the countries, though not always in dating the start of inflation targeting experiences

(2) They follow Mishkin and Schmidt-Hebbel (2001) except when some central banks suggested other starting dates

(3) Authors' notes: South Africa established the first inflation target for 2002

(4) Dates obtained from the figures that show both the inflation series and the inflation targets. The dates corresponding to Norway and Switzerland have been obtained from the text

(5) Sources: Fracasso et al. (2003), Truman (2003), Pétursson (2004), Mishkin and Schmidt-Hebbel (2001), Schaechter et al. (2000), and central bank web pages.

(7) Sources: Central banks websites and publications, discussions with central banks and Bernanke and others (1999)

(8) Switzerland was intentionally excluded (by the author) based on the self-declaration as NITer. See Truman (2003) and Schmidt-Hebbel and Tapia (2002)

(11) If the Inflation Targeting adoption date is July or later of any year t, the annual date reported is year t+1

PP=IT partial adoption, FF=IT fully-fledged adoption, and ST=stationary period according to the definition of inflation targets

Table 4: **Determinants of IT Regime Likelihood**

Variable	Description	Source	Expected signs	Estimated signs
Normalized Inflation rate	$\pi/(1+\pi)$ π: CPI inflation rate	WDI (2007)	Negative	Negative
Government budget balance	Overall Government Budget Balance (surplus)/GDP	GFS and EIU	Positive	Positive
Financial development	Domestic credit to private sector/GDP	WDI (2007)	Positive	Positive
GDP per capita	Natural Log of the GDP per capita	WDI (2007)	Positive	Positive
Trade openness	(X+M)/GDP	WDI (2007)	Positive	Positive

EIU: The Economist Intelligence Unit, GFS: Government Financial Statistics, WDI: World Development Indicators.

Table 5: **Country Sample according to Income Category**

income country group	2	3	4	5
Inflation targeters				
	Brazil (BRA)	Chile (CHL)	Australia (AUS)	Israel (ISR)
	Colombia (COL)	Czech Republic (CZE)	Canada (CAN)	
	Guatemala (GTM)	Hungary (HUN)	Switzerland (CHE)	
	Indonesia (IDN)	Mexico (MEX)	United Kingdom (GBR)	
	Peru (PER)	Poland (POL)	Iceland (ISL)	
	Philippines (PHL)	Romania (ROM)	South Korea (KOR)	
	Thailand (THA)	Slovak Republic (SVK)	Norway (NOR)	
		South Africa (ZAF)	New Zealand (NZL)	
			Sweden (SWE)	

2, 3, 4 and 5 stands for lower middle income, upper middle income, high income OECD, and high income non-OECD countries.

Table 6: **Pair-wise Correlation Analysis**

Sample	Dummy IT	Inflation rate	Budget balance	Financial development	GDP per capita	Trade openness
Dummy IT	1	-0.1029*	-0.2236*	0.3374*	0.4551*	-0.1626*
Inflation rate	-0.3265*	1	-0.5247*	-0.5427*	-0.3363*	-0.4453*
Budget balance	0.2433*	-0.5179*	1	0.0677	0.0342	0.1193*
Financial development	0.3136*	-0.3821*	0.1684*	1	0.6132*	0.2947*
GDP per capita	0.2972*	-0.2880*	0.0834	0.5864*	1	0.3268*
Trade openness	0.1467*	-0.3309*	0.0857	0.2906*	0.3195*	1

Numbers in the inferior triangle are the pooled correlations across the time and countries (pooled correlations) while the numbers in the superior triangle are cross correlations across countries (among time-demeaned variables). * denotes significance at 5% at maximum.

Table 7: **Panel ANOVA Analysis**

	Inflation rate	Budget balance	Financial development	GDP per capita	Trade openness
Sample: 1975-2005					
within variance (%)	0.4480	0.6018	0.2791	0.0537	0.2532
between variance (%)	0.5520	0.3982	0.7209	0.9463	0.7468

Table 8: **Model Selection based on Information Criteria: Logit Models**

Model		*1*	*2*	*3*	*4*	*5*					
AIC	$k = 1$	-0.504	-0.874	-0.699	-0.519	-0.893					
BIC		-0.327	-0.696	-0.522	-0.342	-0.715					
HQC		-0.435	-0.804	-0.630	-0.449	-0.823					
Model		*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*
AIC	$k = 2$	-0.483	-0.358	-0.326	-0.410	-0.607	-0.482	-0.651	-0.419	-0.603	-0.490
BIC		-0.297	-0.172	-0.140	-0.224	-0.421	-0.296	-0.466	-0.233	-0.417	-0.304
HQC		-0.410	-0.285	-0.253	-0.337	-0.534	-0.409	-0.578	-0.346	-0.530	-0.417
Model		*16*	*17*	*18*	*19*	*20*	*21*	*22*	*23*	*24*	*25*
AIC	$k = 3$	-0.352	-0.321	-0.382	-0.261	-0.257	-0.314	-0.394	-0.458	-0.445	-0.379
BIC		-0.158	-0.127	-0.188	-0.067	-0.063	-0.120	-0.200	-0.264	-0.251	-0.185
HQC		-0.276	-0.245	-0.306	-0.185	-0.181	-0.238	-0.318	-0.382	-0.369	-0.303
Model		*26*	*27*	*28*	*29*	*30*					
AIC	$k = 4$	-0.255	-0.245	-0.305	-0.216	-0.345					
BIC		-0.053	-0.043	-0.103	-0.013	-0.143					
HQC		-0.176	-0.166	-0.226	-0.136	-0.266					
Model		*31*									
AIC	$k = 5$	**-0.212**									
BIC		**-0.001**									
HQC		**-0.129**									

AIC: Akaike information criterion, BIC: Schwarz informatio criterion, HQC: Hannan-Quinn information criterion. All models were estimated using the same sample. k denotes the number of variables whose combination produce the models shown in each column. For example, from $k = 2$ it is possible to form 10 models.

Table 9: **Model Selection based on Information Criteria: Probit Models**

Model		*1*	*2*	*3*	*4*	*5*					
AIC	$k=1$	-0.605	-0.878	-0.707	-0.529	-0.894					
BIC		-0.428	-0.701	-0.529	-0.351	-0.716					
HQC		-0.536	-0.808	-0.637	-0.459	-0.824					
Model		*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*
AIC	$k=2$	-0.577	-0.401	-0.402	-0.490	-0.616	-0.487	-0.652	-0.432	-0.605	-0.500
BIC		-0.391	-0.216	-0.216	-0.304	-0.430	-0.302	-0.466	-0.246	-0.419	-0.314
HQC		-0.504	-0.328	-0.329	-0.417	-0.543	-0.414	-0.579	-0.359	-0.532	-0.427
Model		*16*	*17*	*18*	*19*	*20*	*21*	*22*	*23*	*24*	*25*
AIC	$k=3$	-0.396	-0.394	-0.449	-0.309	-0.309	-0.378	-0.406	-0.461	-0.449	-0.394
BIC		-0.202	-0.200	-0.255	-0.115	-0.115	-0.183	-0.211	-0.266	-0.255	-0.200
HQC		-0.320	-0.318	-0.373	-0.233	-0.233	-0.301	-0.329	-0.384	-0.373	-0.317
Model		*26*	*27*	*28*	*29*	*30*					
AIC	$k=4$	-0.305	-0.296	-0.365	-0.265	-0.355					
BIC		-0.102	-0.094	-0.163	-0.063	-0.153					
HQC		-0.225	-0.217	-0.286	-0.186	-0.276					
Model		*31*									
AIC	$k=5$	**-0.260**									
BIC		**-0.049**									
HQC		**-0.177**									

AIC: Akaike information criterion, BIC: Schwarz informatio criterion, HQC: Hannan-Quinn information criterion. All models were estimated using the same sample. k denotes the number of variables whose combination produce the models shown in each column. For example, from $k = 2$ it is possible to form 10 models.

Table 10: **Bonferroni p-value Bounds for the Multiple Non-significance Hypothesis**

Model	$k=1$	*1*	*2*	*3*	*4*	*5*					
p-value		0.036	0.114	0.000	0.000	0.000					
Model	$k=2$	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*
p-value		0.030	0.012	0.000	0.011	0.006	0.000	0.002	0.000	0.000	0.002
Model	$k=3$	*16*	*17*	*18*	*19*	*20*	*21*	*22*	*23*	*24*	*25*
p-value		0.013	0.449	0.009	0.000	0.016	0.040	0.002	0.000	0.001	0.000
Model	$k=4$	*26*	*27*	*28*	*29*	*30*					
p-value		0.341	0.010	0.044	0.002	0.000					
Model	$k=5$	*31*									
p-value		0.008									

Hochberg (1988)' method consists in ordering the p-values from testing m hypothesis as $p_{(1)}, \ldots, p_{(m)}$ and computing the bound as $B = \min_{i \in \{1,\ldots,m\}} (m - i + 1) p_{(i)}$. All models were estimated using the same sample. k denotes the number of variables whose combination produce the models shown in each column. For example, from $k = 2$ it is possible to form 15 models.

Table 11: **Estimation Results: 5-year-based estimations**

	Baseline regression				**Alternative regression**			
Logit Regression	parameter estimates	p-value	marginal effects	p-value	parameter estimates	p-value	marginal effects	p-value
CPI inflation	-28.056	0.040	-1.302	0.006	-29.691	0.039	-1.121	0.006
budget balance	1.799	0.838	0.083	0.879	–	–	–	–
financial development	14.643	0.000	0.679	0.002	14.118	0.000	0.533	0.002
GDP per capita	11.782	0.020	0.547	0.017	13.845	0.006	0.523	0.012
trade openness	19.003	0.001	0.882	0.006	21.684	0.001	0.819	0.003
Ho: $\eta_i = 0 \quad i = 1, \ldots, N$	LM test	5965.67	p-value	0.000	LM test	37238.89	p-value	0.000
Probit Regression	parameter estimates	p-value	marginal effects	p-value	parameter estimates	p-value	marginal effects	p-value
CPI inflation	-8.778	0.008	-1.620	0.000	-9.115	0.006	-1.546	0.000
budget balance	3.620	0.330	0.668	0.497	–	–	–	–
financial development	6.662	0.000	1.230	0.000	6.213	0.000	1.054	0.000
GDP per capita	5.383	0.001	0.994	0.001	6.381	0.000	1.083	0.001
trade openness	7.839	0.000	1.447	0.000	8.734	0.000	1.482	0.000
Ho: $\eta_i = 0 \quad i = 1, \ldots, N$	LM test	4113.14	p-value	0.000	LM test	38333.88	p-value	0.000

Estimated individual effects not reported.

Table 12: **Marginal Contribution of Key Determinants of IT Regime Likelihood**

Variable	Marginal contribution	Measure	Impact of ...
CPI inflation rate	13.19%	$\pi^n = \pi/(1+\pi)$	a reduction of π^n in 10 percentage points (p.p.) which amounts roughly a reduction of π from 17% to 5%
Financial development	6.79%	ratio	an increase of the indicator in 10 p.p.
GDP per capita	65.64%	in logs	an increase of the log of GDP per capita in 1.2 which accounts for passing from 2 (8.1 Indonesia) to 3 (9.3 Poland) in income category
Trade openness	8.82%	ratio	an increase of the indicator in 10 p.p.

The figures for Indonesia and Poland correspond to averages of the log of GDP per capita computed over the period 2001-2005. For income categories see table 5.

Table 13: **Estimation Results: 3-year-based estimations**

	Baseline regression				**Alternative regression**			
Logit Regression	parameter estimates	p-value	marginal effects	p-value	parameter estimates	p-value	marginal effects	p-value
CPI inflation	-51.159	0.000	-0.367	0.088	-51.900	0.000	-0.389	0.089
budget balance	-11.163	0.312	-0.080	0.374	–	–	–	–
financial development	12.141	0.000	0.087	0.108	11.864	0.000	0.089	0.113
GDP per capita	16.184	0.002	0.116	0.094	14.234	0.003	0.107	0.098
trade openness	20.374	0.000	0.146	0.114	21.403	0.000	0.160	0.116
Probit Regression	parameter estimates	p-value	marginal effects	p-value	parameter estimates	p-value	marginal effects	p-value
CPI inflation	-18.345	0.000	-1.261	0.003	-18.390	0.000	-1.271	0.003
budget balance	-2.088	0.670	-0.143	0.672	–	–	–	–
financial development	5.586	0.000	0.384	0.005	5.551	0.000	0.384	0.005
GDP per capita	5.394	0.002	0.371	0.025	5.108	0.001	0.353	0.024
trade openness	8.948	0.000	0.615	0.006	9.198	0.000	0.636	0.005

Estimated individual effects not reported.

Table 14: **Estimation Results: 4-year-based estimations**

	Baseline regression				**Alternative regression**			
Logit Regression	parameter estimates	p-value	marginal effects	p-value	parameter estimates	p-value	marginal effects	p-value
CPI inflation	-37.868	0.000	-0.896	0.030	-37.838	0.000	-0.922	0.028
budget balance	-7.271	0.518	-0.172	0.524	–	–	–	–
financial development	13.041	0.000	0.308	0.037	12.932	0.000	0.315	0.036
GDP per capita	13.637	0.002	0.323	0.049	12.453	0.001	0.303	0.050
trade openness	18.238	0.000	0.431	0.049	19.135	0.000	0.466	0.042
Probit Regression	parameter estimates	p-value	marginal effects	p-value	parameter estimates	p-value	marginal effects	p-value
CPI inflation	-11.348	0.000	-1.629	0.000	-11.345	0.000	-1.629	0.000
budget balance	-0.105	0.983	-0.015	0.983	–	–	–	–
financial development	5.978	0.000	0.858	0.000	5.976	0.000	0.858	0.000
GDP per capita	5.528	0.001	0.794	0.002	5.515	0.000	0.792	0.001
trade openness	7.812	0.000	1.121	0.000	7.826	0.000	1.124	0.000

Estimated individual effects not reported.

Table 15: **Estimation Results: 6-year-based estimations**

	Baseline regression				**Alternative regression**			
Logit Regression	parameter estimates	p-value	marginal effects	p-value	parameter estimates	p-value	marginal effects	p-value
CPI inflation	-22.377	0.000	-1.569	0.005	-22.996	0.000	-1.617	0.005
budget balance	12.418	0.317	0.871	0.328	–	–	–	–
financial development	16.361	0.000	1.147	0.000	16.156	0.000	1.136	0.000
GDP per capita	10.900	0.007	0.764	0.017	12.517	0.001	0.880	0.005
trade openness	19.462	0.000	1.365	0.003	17.039	0.000	1.198	0.002
Probit Regression	parameter estimates	p-value	marginal effects	p-value	parameter estimates	p-value	marginal effects	p-value
CPI inflation	-7.427	0.000	-1.600	0.001	- 8.094	0.000	-1.742	0.000
budget balance	8.510	0.150	1.833	0.157	–	–	–	–
financial development	7.542	0.000	1.624	0.000	7.562	0.000	1.627	0.000
GDP per capita	5.465	0.002	1.177	0.002	6.227	0.000	1.340	0.000
trade openness	8.385	0.000	1.806	0.000	6.919	0.000	1.489	0.001

Estimated individual effects not reported.

Table 16: **Estimation Results: 7-year-based estimations**

	Baseline regression				**Alternative regression**			
Logit Regression	parameter estimates	p-value	marginal effects	p-value	parameter estimates	p-value	marginal effects	p-value
CPI inflation	-17.764	0.000	-1.611	0.007	-20.004	0.000	-1.866	0.004
budget balance	25.364	0.078	2.301	0.092	–	–	–	–
financial development	20.217	0.000	1.834	0.000	19.203	0.000	1.791	0.000
GDP per capita	10.471	0.011	0.950	0.021	13.272	0.001	1.238	0.002
trade openness	21.087	0.001	1.913	0.003	15.618	0.001	1.457	0.005
Probit Regression	parameter estimates	p-value	marginal effects	p-value	parameter estimates	p-value	marginal effects	p-value
CPI inflation	-6.678	0.000	-1.582	0.001	-8.036	0.000	-1.928	0.000
budget balance	15.261	0.035	3.615	0.038	–	–	–	–
financial development	9.482	0.000	2.246	0.000	9.236	0.000	2.216	0.000
GDP per capita	5.366	0.005	1.271	0.006	6.615	0.000	1.587	0.000
trade openness	9.772	0.001	2.315	0.001	6.792	0.002	1.629	0.003

Estimated individual effects not reported.